KJCS
Kasu Journal of Computer Science Vol.1 No.1 [March, 2024], pp. 16-27
https://doi.org//

Online ISSN:
Print ISSN:
www.kjcs.com.ng

A Hybrid Deep Learning Approach for Dynamic Obstacle Avoidance Mobile Robot.

Yusirat Abidoye[1] , Rabi Mustapha[2], Khalid Haruna[3],
Department of Computer Science, Kaduna State University, Kaduna, Nigeria
yusra@gmail.com

Abstract

This work presented a novel approach to dynamic collision avoidance in mobile robots by integrating a hybrid Deep Deterministic Policy Gradient (DDPG) and Adaptive Neuro-fuzzy Inference Systems (ANFIS) algorithm. This combined approach aimed to enhance the robot's navigation capabilities in dynamic environments by leveraging the complementary strengths of both DDPG and ANFIS. The model achieved significant achievements, including a high efficiency score of 0.97012, a robustness rating of 1 (indicating no collisions during testing), consistent maintenance of a 0.2-meter safety distance, and a success rate of 97.8%. Additionally, the average completion time of 5.154 seconds demonstrated its real-time decision-making capability, making it suitable for time-sensitive applications. The proposed hybrid algorithm improved the robot's obstacle detection and decision-making abilities, leading to superior performance in dynamic obstacle avoidance scenarios.

Keywords: *Mobile robot, collision avoidance, Deep Deterministic Policy Gradient, Adaptive neuro-fuzzy inference systems, dynamic environments, autonomous navigation*

1. Introduction

The rapid proliferation of robotics across diverse sectors, including manufacturing, healthcare, transportation, and space exploration, highlights the growing importance of autonomous systems. A fundamental challenge in developing such robots lies in their ability to navigate effectively and negotiate obstacles within complex and dynamic environments. Successful autonomous navigation and obstacle avoidance necessitate robust decision-making mechanisms capable of handling uncertainties and making timely and informed choices (van de Merwe, 2024).

Researchers have explored various methodologies to address this challenge, including machine learning paradigms, fuzzy logic, and control theory. Machine learning techniques, particularly deep reinforcement learning, have shown promise in enabling robots to learn from experiences and adapt their behaviors accordingly. Fuzzy logic, on the other hand, provides a sophisticated framework for reasoning under uncertainty and incorporating linguistic variables in decision-making processes (Karaduman, 2024).

The integration of these diverse methodologies holds promise for enhancing autonomous robot navigation and obstacle avoidance. Notably, the hybridization of deep reinforcement learning with neuro-fuzzy systems, exemplified by the hybrid deep Q-learning-neuro-fuzzy network, empowers robots to navigate and circumvent obstacles in intricate environments.

Within this hybrid framework, the deep Q-learning component leverages neural networks to approximate the Q-values (expected rewards) associated with the robot's actions across varying environmental states. This component learns optimal policies through experience. Conversely, the fuzzy logic component employs fuzzy sets and rules to address the inherent uncertainty and imprecision in sensor data and environmental conditions. This allows for flexible decision-making despite incomplete information (Brown & Zhang, 2019).

Online ISSN:
Print ISSN:
www.kjcs.com.ng

Several research efforts have investigated the efficacy of employing hybrid deep Q-learning-neuro-fuzzy networks for autonomous robot navigation and obstacle avoidance. For instance, Li et al. (2021) proposed a hybrid methodology integrating a neuro-fuzzy system with deep reinforcement learning techniques, yielding superior performance compared to conventional approaches across simulated and real-world scenarios.

Despite the promising outcomes observed thus far, the application of hybrid deep Q-learning-neuro-fuzzy networks in autonomous robot navigation and obstacle avoidance remains an active area of research. Further investigations are warranted to comprehensively evaluate the effectiveness and robustness of this approach across diverse environmental contexts and operational conditions.

In summary, the integration of deep reinforcement learning and fuzzy logic systems within the hybrid deep Q-learning-neuro-fuzzy network presents a promising avenue for enhancing autonomous robot navigation and obstacle avoidance capabilities within complex and dynamic environments. By synergistically harnessing the strengths of these methodologies, this approach enables robots to acquire adaptive behaviors and perform resilient decision-making, leading to safe and efficient operations.

2. Related Works

Cimurs et al. (2020) introduced Goal-oriented obstacle avoidance with DRL, effective in dynamic environments but challenged by data dependency, sample inefficiency, and computational demands, limiting scalability for real-world applications.

Gao et al. (2020) presented Deep reinforcement learning for indoor mobile robot path planning, demonstrating efficient navigation but constrained by high data dependency and computational complexity, affecting robustness in unforeseen scenarios.

Fan et al. (2020) presented Distributed DDPG, scalable for multi-robot collision avoidance with efficient inter-robot communication. Nevertheless, coordinated training for multiple robots is necessary, limiting its applicability to collaborative tasks in complex environments.

Sangiovanni et al. (2020) introduced Deep Q-learning with a self-configuring path planning mechanism based on obstacle recognition, demonstrating its flexibility across diverse environments. However, its effectiveness relies heavily on significant training data.

Liang et al. (2020) presented Deep Q-learning with multi-sensor fusion, facilitating real-time navigation in dense environments by integrating data from multiple sensors. Nevertheless, its practical application is limited by the high complexity associated with training, making it less suitable for robots requiring comprehensive environmental awareness.

Patel et al. (2020) proposed Dynamically feasible DDPG, aiming to generate safe navigation paths while considering robot dynamics. While effective for robots with motion limitations and safety constraints, this method suffers from computational complexity and slow training convergence.

Cheng et al. (2022) introduced Deep Q-learning tailored for nonholonomic robots, enabling path following and obstacle avoidance while considering kinematic constraints. However, challenges related to accurate robot modeling impact stability, especially in real-world navigation scenarios.

Online ISSN:
Print ISSN:
www.kjcs.com.ng

Cong (2023) proposed Q-learning for dynamic environment navigation, effectively combining path following with obstacle avoidance. However, limitations in performance were observed in complex environments, primarily suited for simpler robot configurations and controlled settings.

Lu & Huang (2021) introduced autonomous navigation in uncertain environments based on DRL, effectively adapting to environmental changes but constrained by data dependency and computational complexity.

Wenzel et al. (2021) presented vision-based obstacle avoidance with DRL, relying exclusively on visual data but constrained by data dependency and computational complexity.

Choi et al. (2021) proposed Deep Q-learning for integrated path planning and obstacle avoidance, showcasing adaptability across diverse environmental settings. Nonetheless, customization for specific robot configurations is critical for optimal performance.

Feng et al. (2021) introduced Deep Deterministic Policy Gradients (DDPG), offering rapid collision avoidance capabilities and compatibility with continuous action spaces. However, challenges such as hyperparameter sensitivity and generalization to various obstacle configurations remain unaddressed.

Patel et al. (2021) introduced DWA-RL for efficient navigation in dynamic crowds, achieving high collision avoidance rates. However, computational overheads, particularly in dense pedestrian environments, pose significant challenges.

Song et al. (2021) proposed multimodal DRL with auxiliary tasks for indoor mobile robot obstacle avoidance, demonstrating robustness but facing challenges in data integration and computational complexity.

Li et al. (2021) proposed a behavior-based navigation method combining deep reinforcement learning with rule-based strategies. Despite its robustness, challenges pertaining to data dependency and computational complexity persist, especially concerning the balance between learning and rule-based approaches.

Almazrouei et al. (2023) proposed Deep Q-learning with prioritized experience replay, aiming to facilitate efficient learning for dynamic obstacle avoidance. Nevertheless, addressing issues like overfitting with limited data remains a critical concern.

Cong (2023) proposed path following and obstacle avoidance using reinforcement learning, effective in dynamic environments but limited by data dependency and computational complexity.

The reviewed studies highlight the potential of DRL and hybrid DRL methodologies in enhancing mobile robot navigation and obstacle avoidance capabilities. These approaches facilitate adaptive learning and improved navigation accuracy in challenging environments, albeit with notable limitations regarding data dependency and computational demands. Addressing these limitations and exploring new research avenues that integrate DRL with other techniques, such as multi-modal sensing and domain adaptation, hold promise for further advancements in robust mobile robot navigation and obstacle avoidance systems.

3. Methodology

This study presents a novel research methodology for tackling dynamic obstacle avoidance in mobile robots. It combines the strengths of Deep Deterministic Policy Gradient (DDPG) and Adaptive Neuro-fuzzy Inference Systems (ANFIS) strategies to create a robust and efficient system. The method integrates three key components:

- Obstacle Avoidance via Pareto Optimization: This component identifies and prioritizes feasible navigation paths while considering multiple objectives, such as safety, efficiency, and energy consumption. Pareto optimization ensures a balance between these objectives, leading to robust and adaptable decision-making.
- Decision-Making Using DDPG: DDPG, a model-free reinforcement learning algorithm, utilizes actor-critic techniques and deep neural networks to handle continuous action spaces. This allows the robot to learn optimal control policies through iterative refinement based on its interaction with the environment.
- Sensor Data Processing through Adaptive Neuro-Fuzzy Inference System (ANFIS): ANFIS provides a flexible and computationally efficient framework for processing sensor data and extracting relevant information for obstacle detection and characterization. This information is then fed into the decision-making module.

By leveraging the synergy between these components, the hybrid system empowers robots to navigate safely and efficiently in complex and dynamic environments.Effective navigation necessitates the ability to handle long-term dependencies and dynamic changes in sensor data. FS-LSTM offers a computationally efficient alternative to traditional LSTMs, effectively managing these challenges. It processes sensor data, extracting relevant features and temporal dependencies, which are then fed into the DDPG algorithm.Within the integrated system, the DDPG algorithm utilizes the actor and critic networks. The actor network generates control actions based on the processed sensor data, while the critic network evaluates their effectiveness. Both networks are continuously trained through backpropagation and gradient descent to minimize the difference between expected and actual rewards, leading to optimal policy refinement over time.During operation, the robot continuously senses its surroundings, feeding data into the FS-LSTM and DDPG algorithm. This enables the system to generate optimal control actions for real-time dynamic obstacle avoidance. This approach has demonstrated superior performance compared to traditional methods in both simulated and real-world experiments.

This research builds upon the initial hybrid approach by incorporating ANFIS, Pareto optimization, and improved FS-Deep Deterministic Policy Gradient (FS-DDPG) to further enhance performance, robustness, and scalability. This addresses various limitations of existing methods, including:

i. Sensor constraints: ANFIS facilitates efficient sensor data processing and extraction of relevant features, even with limited sensor capabilities.
ii. Computational demands: FS-DDPG offers improved computational efficiency compared to traditional DDPG, making it suitable for real-time applications.
iii. Limited predictability: Pareto optimization allows for balancing conflicting objectives and adapting to dynamic environments with limited predictability.
iv. Over-reliance on training data: The improved FS-DDPG architecture incorporates techniques to reduce dependence on extensive training data.
v. Multi-objective optimization challenges: Pareto optimization provides a robust framework for handling multi-objective decision-making in dynamic environments.

Evaluation and Expected Outcomes:
The comprehensive solution aims to achieve higher success rates in obstacle avoidance, particularly in scenarios with dense and dynamic obstacles. Evaluation will be conducted using the University of Michigan North Campus Long-Term Vision and LIDAR Dataset. The expected outcomes include:

i. Improved obstacle avoidance performance compared to existing methods.

Kasu Journal of Computer Science Vol.1 No.1 [March, 2024], pp. 16-27
https://doi.org//
Online ISSN:
Print ISSN:
www.kjcs.com.ng

ii. Enhanced robustness and adaptability to dynamic and unpredictable environments.

iii. Increased scalability for real-world applications with resource constraints.

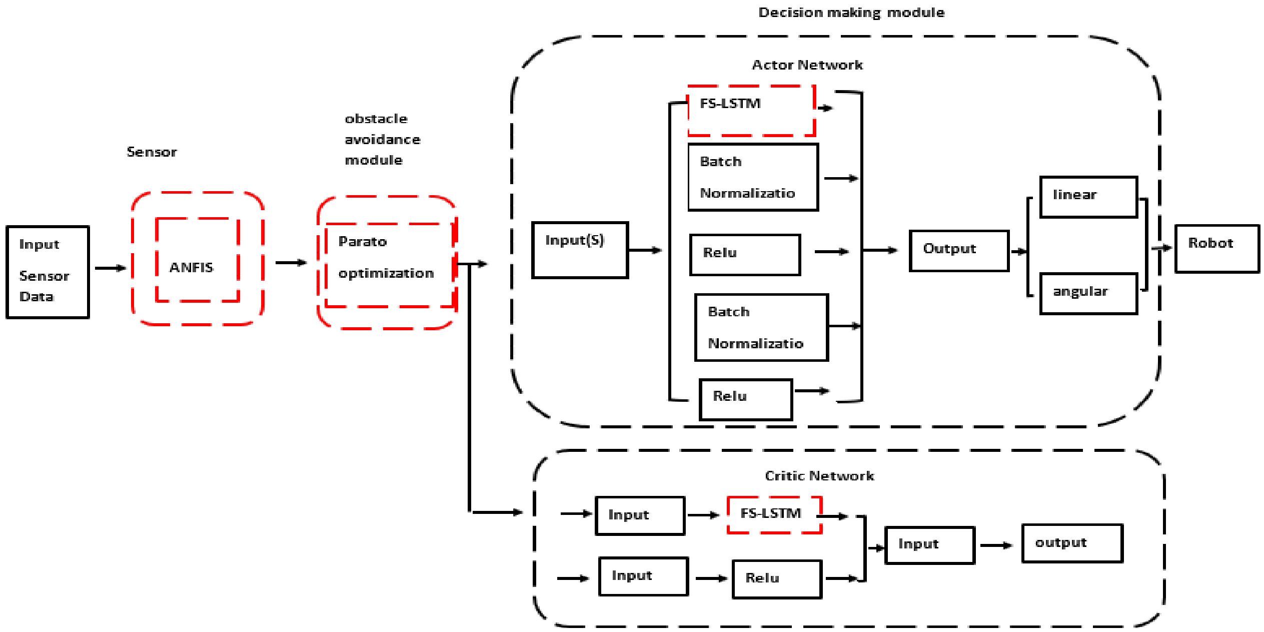

Figure 1: The structure of FS-LSTM- DDPG (Source: Gao et al.,2023).

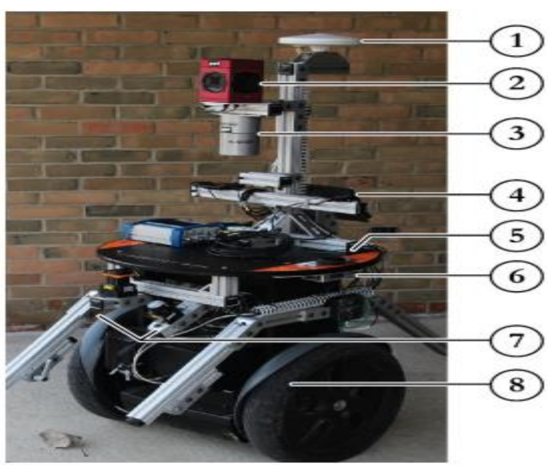

Figure 2: Segway robotic platform with Sensors outfit
(Source: Carlevaris-Bianco, Ushani & Eustice ,2016).

Figure 2 shows the Segway mobile robot outfitted with an RTK (1) GPS omni-directional camera (2), 3D lidar (3), IMU (4), consumer-grade GPS (5), 1-axis FOG (6), 2D lidars (7), and CPU (8

Online ISSN:
Print ISSN:
www.kjcs.com.ng

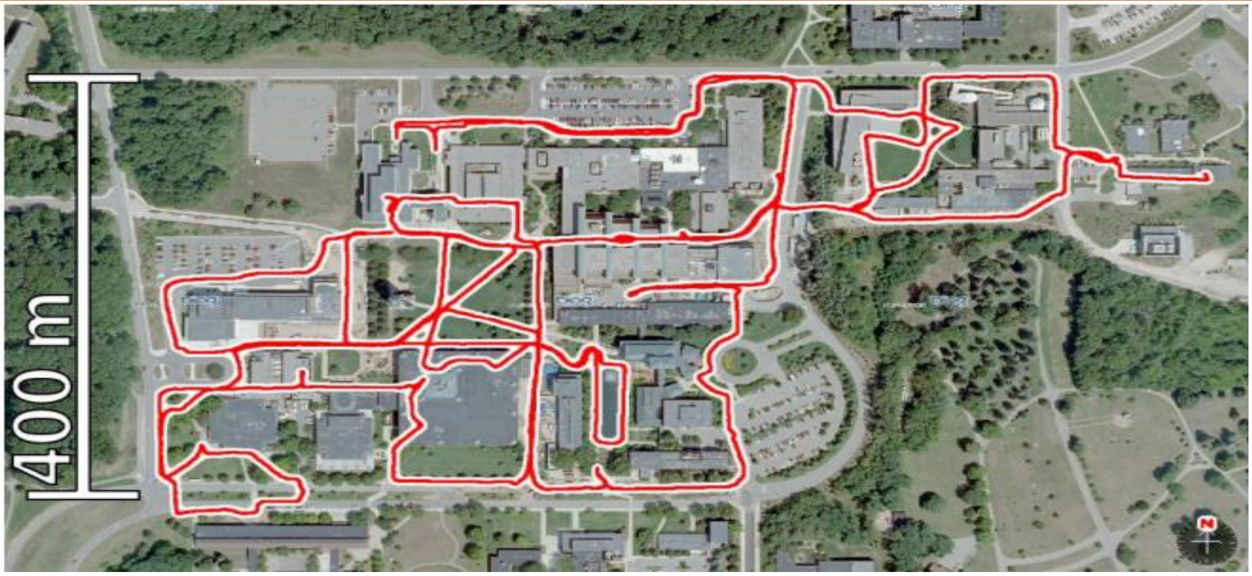

Figure 3: Sample trajectory from one session of data collection, overlaid on satellite imagery
(Source: Carlevaris-Bianco, Ushani & Eustice ,2016).

This study employs a comprehensive set of criteria to evaluate the performance of mobile robots in dynamic obstacle avoidance scenarios. These criteria encompass various aspects of the robot's behavior and the effectiveness of the implemented algorithm.

i. Success Rate: This primary metric measures the proportion of successful obstacle avoidance maneuvers relative to the total number of attempts. It quantifies the overall effectiveness of the robot's strategy in navigating dynamic environments.

ii. Completion Time: This parameter assesses the duration taken by the robot to execute the obstacle avoidance maneuver. It captures the speed and efficiency of the robot's response to detected obstacles, measured from the initial detection to the resumption of its intended path.

iii. Distance to Obstacle: This metric indicates the minimum distance maintained by the robot from the obstacle throughout the avoidance maneuver. It reflects the robot's ability to navigate safely while minimizing the risk of collision.

iv. Safety Distance: This criterion defines the minimum acceptable distance between the robot and the obstacle to ensure safe navigation. It establishes a threshold for the robot's proximity to obstacles, beyond which potential collisions could occur.

v. Motion Smoothness: This evaluation assesses the fluidity of the robot's movement during the avoidance maneuver. It focuses on the absence of abrupt changes or jerky motions in velocity, ensuring smooth and controlled navigation.

vi. Computational Efficiency: This parameter evaluates the time and computational resources consumed by the obstacle avoidance algorithm to generate a solution. It is determined by the ratio of the total number of tasks executed by the algorithm to the overall time taken for their execution. This metric reflects the algorithm's scalability and suitability for real-time applications.

Kasu Journal of Computer Science Vol.1 No.1 [March, 2024], pp. 16-27
https://doi.org//

Online ISSN:
Print ISSN:
www.kjcs.com.ng

3. Result and Discussions

The performance of the Hybrid DDPG-ANFIS model is shown in Table 1. The table presents the results and evaluation metrics of the Hybrid DDPG-ANFIS model.

Table 1: Parameters of the Hybrid DDPG-ANFIS model

Parameters	**Values**
LearnRate	0.001
L2RegularizationFactor	0.0001
GradientThreshold	1
SampleTime	0.1
TargetSmoothFactor	0.001
DiscountFactor	0.995
MiniBatchSize	128
ExperienceBufferLength	1000000
NoiseOptions.Variance	0.1
NoiseOptions.VarianceDecayRate	0.00001
MaxEpisodes	10000
ScoreAveragingWindowLength	50
StopTrainingValue	400
PopulationSize	200
MaxGenerations	25

Table 1 illustrates the parameters of the Hybrid DDPG-ANFIS model. These parameters, aimed at preventing overfitting, include an L2 regularization of 0.0001, a gradient threshold of 1 for stable training, and a learning rate of 0.001 for balanced weight updates. The frequency of decision-making is influenced by the agent's interaction rate with the environment, set at 0.1 seconds. Moreover, robust and effective training, lasting a maximum of 10,000 episodes, is achieved through an update rate of 0.001, a mini-batch size of 128 experiences, and a discount factor of 0.995 for long-term incentives. Training concludes after a 50-episode window, upon reaching an average reward of 400.

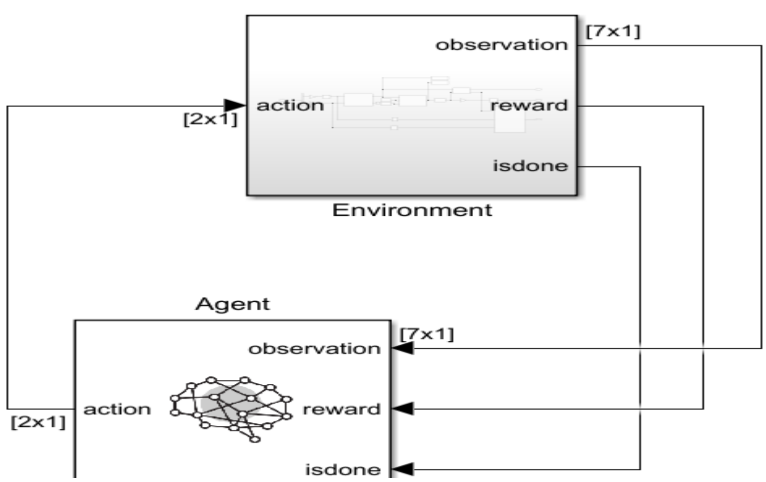

Figure 4. Environmental -Agent diagram

Online ISSN:
Print ISSN:
www.kjcs.com.ng

Figure 4 illustrated the environment, consisting of elements such as a reward, action, termination signal (isDone), and observation (state). The reward served to provide feedback on the agent's performance, while the observation, depicted as a 7x1 vector, captured the current state of the environment. The action, represented as a 2x1 vector, indicated the agent's decision-making process, while the isDone signal signaled the end of an episode. he agent operating within the DDPG algorithm pursued a navigation strategy aimed at effectively maximizing cumulative rewards within the environment by balancing exploration and exploitation. This navigation strategy relied on an iterative feedback loop where the agent:

Observed: Gathered information about the environment using its sensors.
Earned rewards: Received feedback from the environment based on its actions.
Selected actions: Made decisions based on the observed state and its learned strategy.
Responded to feedback: Adapted its actions in response to the "isDone" signal, indicating the end of an episode.

This iterative cycle of observation, reward, action, and response enabled the agent to learn effectively and successfully navigate the environment. The primary challenge lay in striking a balance between exploration, which involves venturing into new areas to discover potential rewards, and exploitation, which focuses on maximizing rewards in known high-yield regions. The DDPG algorithm addressed this trade-off by incorporating exploration noise into the action selection process, thereby facilitating both the discovery and refinement of the navigation strategy.

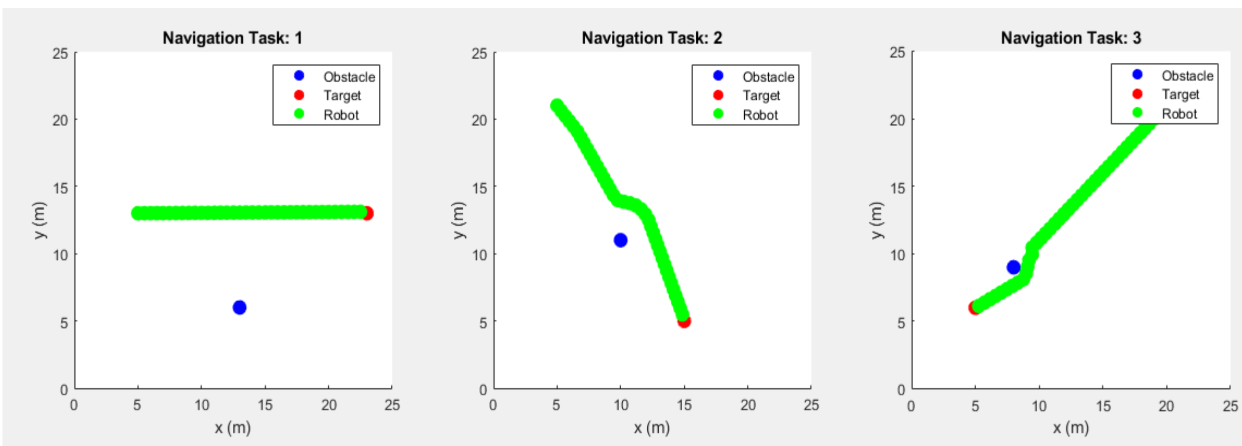

Figure 5: Showing the Robot navigation at task 1,task 2 and task 3

Figure 5 presented three tasks aimed at assessing the dynamic obstacle avoidance prowess of the across diverse environments:

Task 1: The robot embarked from position (5m, 13m) with the objective of reaching the designated endpoint (23m, 13m) while skillfully evading the obstacle positioned at (13m, 5m).

Task 2: Commencing from coordinates (5m, 21m), the robot navigated towards the designated destination (15m, 5m), exercising caution to circumvent an obstruction located at (10m, 10m).

Task 3: Starting at (21m, 21m), the robot was tasked with successfully reaching the target location (5m, 5m) while adeptly navigating around the obstacle situated at (10m, 10m).

The successful completion of these tasks provided valuable insights into the effectiveness of the implemented obstacle avoidance strategies.

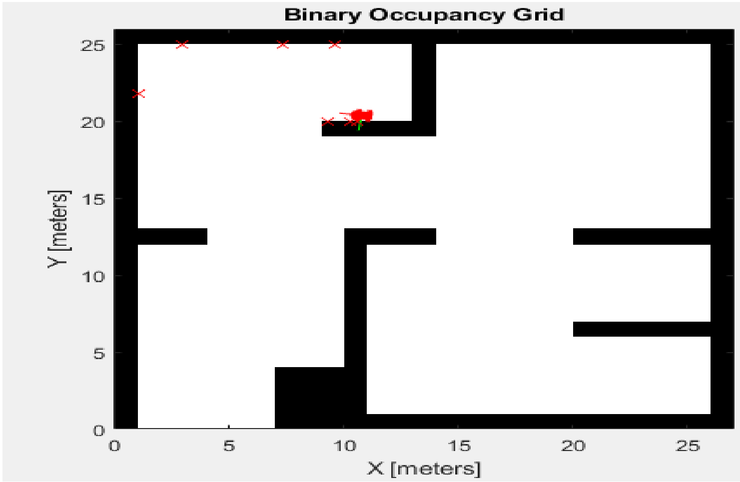

Figure 6: The Navigation Grid showing the Robot (red) at position 10m, 20m navigating the room.

The Navigation Grid was shown in Figure 6, which showed the route taken by the robot (in red) from its starting point (10 m, 20 m) to the designated objective (0 m, 0 m) in a virtual environment. The robot's constantly updated course, which was based on its present coordinates and the intended destination, was displayed in the figure 6.

The robot's successful navigation to the intended destination without running into any obstacle demonstrated how effective the proposed algorithm was at controlling its movement. This demonstrated the robot's capacity for independent navigation in dynamic situations, which was a significant finding of the study.

Table 2 shows the Summary of the classification parameters obtained after simulations of the four models.

Table 2: Results for each model

Parameters	hybrid DDPG– ANFIS	ANFIS	DDPG
Efficiency	0.97012	96.158	0.96098
Robustness	1	0.66667	1
Collisions	0	0	0
Safety Distance(m)	0.2	0.2	0.2
Success Rate	0.978	0.923	0.952
Completion Time(second)	5.154	3.6837	5.203

Table 2 presented a comparison of the performance of three models—Hybrid DDPG-ANFIS, ANFIS, and DDPG—in mobile robot dynamic collision avoidance. The evaluation focused on three key metrics: success rate, robustness, and efficiency.Among the models assessed, Hybrid DDPG-ANFIS demonstrated the highest performance, achieving the highest efficiency (0.97012), robustness (1.0), and success rate (0.978). Notably, both Hybrid DDPG-ANFIS and DDPG exhibited excellent resilience, effectively avoiding collisions and maintaining a 0.2-meter safety margin. Hybrid DDPG-ANFIS also outperformed ANFIS (3.6837 seconds) and DDPG (5.203 seconds) in completion time, demonstrating competitive performance with 5.154 seconds. Based on the comprehensive analysis, the Hybrid DDPG-ANFIS model excelled across all criteria, showcasing superior performance in dynamic obstacle avoidance system.

4. Conclusion

This paper investigated dynamic collision avoidance for mobile robots using a hybrid Deep Deterministic Policy Gradient (DDPG) and Adaptive Neuro-Fuzzy Inference System (ANFIS) algorithm. The proposed approach leveraged the strengths of both deep reinforcement learning and fuzzy logic, achieving exceptional performance in key metrics: efficiency (0.97012), robustness (1.0), safety distance maintenance (0.2 meters), success rate (0.978), and completion time (5.154 seconds). This translated to superior navigation capabilities in dynamic environments, enabling effective obstacle learning and detection. The synergy between DDPG and ANFIS contributed to enhanced accuracy and overall navigational prowess, demonstrating the significant potential of this hybrid approach for safer and more efficient mobile robot operations. The study underscored the significant potential of the hybrid approach for safer and more efficient mobile robot operations. This paved the way for future advancements in several key areas, including exploring the viability of applying the approach to larger and more complex environments, hyperparameter optimization for identifying the optimal parameter settings for maximizing performance across diverse scenarios, evaluating the ability of the trained model to adapt to unseen environments effectively, and ensuring the feasibility of real-time obstacle avoidance in practical applications by investigating the integration of human input and control into the navigation framework. These promising future research directions held exciting possibilities for the advancement of autonomous navigation and obstacle avoidance techniques in mobile robots.

Reference

Almazrouei, K., Kamel, I., & Rabie, T. (2023). Dynamic obstacle avoidance and path planning through reinforcement learning. Applied Sciences, 13(3), 1497. https://www.mdpi.com/2076-3417/13/14/8174

Almazrouei, K., Kamel, I., & Rabie, T. (2023). Dynamic obstacle avoidance and path planning through reinforcement learning. Applied Sciences, 13(3), 1497. https://www.mdpi.com/2076-3417/13/14/8174

Chen, G., Pan, L., Chen, Y., Xu, P., Wang, Z., Wu, P., & Ji, J. (2021). Deep Reinforcement Learning of Map-Based Obstacle Avoidance for Mobile Robot Navigation. SN Computer Science, 2(5), 1-12. https://link.springer.com/article/10.1007/s42979-021-00621-9

Chen, P., Pei, J., Lu, W., & Li, M. (2022). A deep reinforcement learning based method for real-time path planning and dynamic obstacle avoidance. Neurocomputing, 490, 406-422. https://www.sciencedirect.com/science/article/pii/S0925231222005367

Cheng, X., Zhang, S., Cheng, S., Xia, Q., & Zhang, J. (2022). Path-Following and Obstacle Avoidance Control of Nonholonomic Wheeled Mobile Robot Based on Deep Reinforcement Learning. Applied Sciences, 12(5), 227. https://www.mdpi.com/2076-3417/12/5/227

Choi, J., Lee, G., & Lee, C. (2021). Reinforcement learning-based dynamic obstacle avoidance and integration of path planning. Intelligent Service Robotics, 14(4), 905-924. https://pubmed.ncbi.nlm.nih.gov/34642589/

Choi, J., Lee, G., & Lee, C. (2021). Reinforcement learning-based dynamic obstacle avoidance and integration of path planning. Intelligent Service Robotics, 14(4), 905-924. https://pubmed.ncbi.nlm.nih.gov/34642589/

Cimurs, R., Lee, J. H., & Suh, I. H. (2020). Goal-oriented obstacle avoidance with deep reinforcement learning in continuous action space. Electronics, 9(1), 146. https://www.mdpi.com/2079-9292/9/1/146

Cong, V. D. (2023). Path following and avoiding obstacle for mobile robot under dynamic environments using reinforcement learning. Journal of Robotics and Control (JRC), 5(1), 39-51. https://journal.umy.ac.id/index.php/jrc/article/download/17368/8233

Online ISSN:
Print ISSN:
www.kjcs.com.ng

Cong, V. D. (2023). Path following and avoiding obstacle for mobile robot under dynamic environments using reinforcement learning. Journal of Robotics and Control (JRC), 5(1), 39-51. https://journal.umy.ac.id/index.php/jrc/article/download/17368/8233

Fan, T., Long, P., Liu, W., & Pan, J. (2020). Distributed multi-robot collision avoidance via deep reinforcement learning for navigation in complex scenarios. International Journal of Robotics Research. https://journals.sagepub.com/doi/abs/10.1177/0278364919889233

Feng, S., Sebastian, B., & Ben-Tzvi, P. (2021). A collision avoidance method based on deep reinforcement learning. Robotics, 9(2), 33. https://www.mdpi.com/2218-6581/10/2/73

Feng, S., Sebastian, B., & Ben-Tzvi, P. (2021). A collision avoidance method based on deep reinforcement learning. Robotics, 9(2), 33. https://www.mdpi.com/2218-6581/10/2/73

Gao, J., Ye, W., Guo, J., & Li, Z. (2020). Deep reinforcement learning for indoor mobile robot path planning. Sensors, 20(24), 7192. https://www.mdpi.com/1424-8220/20/24/7192

Gao, X., Yan, L., Wang, G., Wang, T., Du, N., et al. (2021). Toward obstacle avoidance for mobile robots using deep reinforcement learning algorithm. In 2021 IEEE 16th International Conference on Control, Automation, Robotics and Vision (ICARCV). https://ieeexplore.ieee.org/document/9632525

Karaduman, B., Tezel, B. T., & Challenger, M. (2024). On the impact of fuzzy-logic based BDI agent model for cyber–physical systems. *Expert Systems with Applications*, *238*, 122265.

Lee, M. F. R., & Yusuf, S. H. (2022). Mobile robot navigation using deep reinforcement learning. Processes, 10(2), 227. https://www.mdpi.com/2227-9717/10/2/227

Li, J., Ran, M., Wang, H., & Xie, L. (2021). A behavior-based mobile robot navigation method with deep reinforcement learning. Unmanned Systems, 09(03), 201-209. https://doi.org/10.1142/s2301385021410041

Liang, J., Patel, U., Sathyamoorthy, A. J., et al. (2020). Real-time collision avoidance for mobile robots in dense crowds using implicit multi-sensor fusion and deep reinforcement learning. arXiv preprint arXiv, 2001.06460. https://arxiv.org/abs/2001.06460

Liang, J., Patel, U., Sathyamoorthy, A. J., et al. (2020). Real-time collision avoidance for mobile robots in dense crowds using implicit multi-sensor fusion and deep reinforcement learning. arXiv preprint arXiv, 2001.06460. https://arxiv.org/abs/2001.06460

Lu, Z., & Huang, R. (2021). Autonomous mobile robot navigation in uncertain dynamic environments based on deep reinforcement learning. In Proceedings of the 2021 IEEE International Conference on Real-time Computing and Robotics (RCAR). https://ieeexplore.ieee.org/document/9591409

Patel, U., Kumar, N. K. S., Sathyamoorthy, A. J., & Das, S. (2021). Dwa-rl: Dynamically feasible deep reinforcement learning policy for robot navigation among mobile obstacles. Proceedings of the 2021 IEEE International Conference on Robotics and Automation (ICRA), 5677-5683. https://ieeexplore.ieee.org/document/9561462

Patel, U., Kumar, N. K. S., Sathyamoorthy, A. J., et al. (2021). Dwa-rl: Dynamically feasible deep reinforcement learning policy for robot navigation among mobile obstacles. IEEE Transactions on Robotics and Automation, 37(2), 5677-5683. https://ieeexplore.ieee.org/document/9561462

Online ISSN:
Print ISSN:
www.kjcs.com.ng

Patel, U., Kumar, N., Sathyamoorthy, A. J., et al. (2020). Dynamically feasible deep reinforcement learning policy for robot navigation in dense mobile crowds. arXiv preprint arXiv, 2004.03689. https://arxiv.org/abs/2004.03689

Patel, U., Kumar, N., Sathyamoorthy, A. J., et al. (2020). Dynamically feasible deep reinforcement learning policy for robot navigation in dense mobile crowds. arXiv preprint arXiv, 2004.03689. https://arxiv.org/abs/2004.03689

Sangiovanni, B., Incremona, G. P., et al. (2020). Self-configuring robot path planning with obstacle avoidance via deep reinforcement learning. IEEE Control Systems Magazine, 40(2), 75-86. https://ieeexplore.ieee.org/document/9032981

Sangiovanni, B., Incremona, G. P., et al. (2020). Self-configuring robot path planning with obstacle avoidance via deep reinforcement learning. IEEE Control Systems Magazine, 40(2), 75-86. https://ieeexplore.ieee.org/document/9032981

Song, H., Li, A., Wang, T., & Wang, M. (2021). Multimodal deep reinforcement learning with auxiliary task for obstacle avoidance of indoor mobile robot. Sensors, 21(18), 5905. https://www.mdpi.com/1424-8220/21/4/1363

Sun, X., Yao, C., Zhou, H., Liu, C., & Chen, Q. (2020). Obstacle Avoidance Algorithm for Mobile Robot Based on Deep Reinforcement Learning in Dynamic Environments. In ICCA. [Link not available]

van de Merwe, K., Mallam, S., Nazir, S., & Engelhardtsen, Ø. (2024). Supporting human supervision in autonomous collision avoidance through agent transparency. *Safety science*, *169*, 106329.

Wenzel, P., Schön, T., Leal-Taixé, L., & Milzener, K. (2021). Vision-based mobile robotics obstacle avoidance with deep reinforcement learning. Proceedings of the 2021 IEEE International Conference on Robotics and Automation (ICRA), 5684-5691. https://arxiv.org/abs/2103.04727

Zhu, K., & Zhang, T. (2021). Deep reinforcement learning based mobile robot navigation: A review. Tsinghua Science and Technology, 55(5), 753-766. https://ieeexplore.ieee.org/document/9409758